Journal of Cleaner Production 197 (2018) 895–907

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Environmental efficiency analysis and estimation of CO_2 abatement costs in dairy cattle farms in Umbria (Italy): A SBM-DEA model with undesirable output

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A R T I C L E I N F O

Article history:
Received 17 February 2018
Received in revised form
21 May 2018
Accepted 14 June 2018
Available online 22 June 2018

Keywords:
Greenhouse gas emissions
Slacks-based measure-data envelopment analysis
Environmental efficiency
Dairy production

A B S T R A C T

Livestock activity is one of the most contributors to climate-change emissions in the agriculture sector. European environmental policies face with the challenge of increasing farmers economic gain not conflicting with environmental aim at the same time, to meet targets for reducing greenhouse gas emissions (GHG). The paper aims to contribute to the discussion on CO_2 emission mitigation by providing efficiency performance measures in the presence of joint production of milk and GHG emissions.

A Slacks-Based Measure-Data Envelopment Analysis (SBM-DEA) with undesirable output was adopted and integrated with Life Cycle Analysis (LCA) results from 10 dairy cattle farms in Umbria (Italy) to estimate their environmental efficiency and emission reduction potential. In addition, the dual model of the SBM-DEA was used to quantify the marginal CO_2 reduction costs. Four farms resulted in no CO_2-eq emission efficient, with a reduction potential ranging from 45.7% to 26.3% of CO_2-eq. An average abatement cost of € 243.08 in terms of lower milk production per ton of CO_2-eq reduced, was estimated for the whole sample. A positive relationship between marginal abatement costs and CO_2-eq efficiency scores was estimated. Marginal abatement costs knowledge could allow assessing the economic impacts of different farms strategies aimed at reducing polluting emissions, as well as the introduction of incentive mechanisms by public decision makers.

1. Introduction

In line with the growing global awareness of environmental protection issues, the focus of researchers and institutions has been increasingly concentrating on the study of undesirable output associated with production processes, which is now universally recognized as a central role in influencing the integrity of ecosystems and human health. In this regard, over the last few years, numerous studies and reports (FAO, 2010; IEA, 2015; IPCC, 2014a; Marchal et al., 2011) have focused on atmospheric pollutants and on Greenhouse Gases (GHG) emissions, which represent the main culprit for the problem of global warming, and the main factor to be addressed through possible mitigation strategies (Huisingh et al., 2015). The agricultural sector has the most significant impact with a contribution of 11% of total global GHG emissions (IPCC, 2014b). Within the agricultural sector, livestock activity contributes 14.5% of GHG emissions, through the emission of carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), globally, (Opio et al., 2013). Particularly significant in the livestock sector, is the contribution of dairy production to polluting emissions, equal to 20% (Opio et al., 2013). In the last decades, different impact assessment studies on cattle dairy system have been conducted to measure the environmental performance and estimate the CO_2-eq emission reduction potential of the sector. Life cycle analysis (LCA) was the most method applied (de Vries and de Boer, 2010; International Dairy Federation, 2009) both at the dairy production level (Bacenetti et al., 2016; Guerci et al., 2014; Zucali et al., 2017) and at macro-scale level (Cecchini et al., 2016; Djekic et al., 2014; Finnegan et al., 2017; Vergé et al., 2009).

Considered a holistic and powerful tool, LCA has been used to quantify a subset of the environmental impacts at farm level including or excluding from the system boundaries some phases of the product life (Zucali et al., 2017), handling multiple input/output data that may strongly influence the evaluation process and results (Vázquez-Rowe et al., 2010).

In some cases, to reduce the emission in one or more process in dairy production system, the increased emission in another part of

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https://doi.org/10.1016/j.jclepro.2018.06.165
0959-6526/

the system happen (Shortall and Barnes, 2013). Also, any strategy aimed at mitigating these impacts, in line with the guidelines outlined in the Europe 2020 strategy (European Commission, 2010), should be based on actions aimed at the environmental efficiency across all dairy system through increasing technical efficiency in the use of inputs (Shortall and Barnes, 2013) and manage output, or undesirable outputs as GHG emissions, simultaneously. In this sense, modelling undesirable outputs in the analysis of the efficiency of production processes takes on increasingly strategic importance in guiding the decisions of the stakeholders involved (farms, public decision-makers and citizens). In this perspective, the paper aims to focus on the relationship between technical efficiency and greenhouse gas emissions, with the purpose of testing the hypothesis that farms which are more technically efficient are also more efficient in their production of greenhouse gases.

The paper has structured into four sections. After reviewing the literature on DEA models, section 2 describes the methodology used in the research by illustrating the theoretical method and going into the depth of the analytical foundations of the SBM-DEA model. A detailed description of both data collection and carried out analysis, is reported in the methodological section. In section 3, the results and discussion are presented. In the last part, an overview of the study outcomes and the potential implications of policies are reported as well as suggestions for further research.

1.1. Literature review

From the analysis of the literature, techniques of estimation of efficiency, which are calculated as the distance from the theoretical efficiency frontier, can be traced back to two fundamental approaches. The first method concerns the parametric formulation, which includes different variations concerning the functional form of the distance function. The second approach is about the non-parametric technique represented by the Data Envelopment Analysis (DEA) (Choi et al., 2012).

In general, DEA is a methodology that uses linear programming techniques to determine the relative efficiency of production units or similar decision-making units (DMUs) (Charnes et al., 1994). Its nonparametric approach favours its flexibility of application, since it is not necessary to explicitly specify *a priori* a production function that explains how the inputs and outputs of the production units are linked to each other. The origin of DEA dates to 1978, thanks to the work of Charnes et al. (1978) who used mathematical programming in extending the studies conducted by Farrell (1957). The basic formulation of DEA assumes a monotonous relationship of linear proportionality between input and output (Charnes et al., 1994), and returns an efficiency score ranging from 0 to 1. The closer the score is to 1, the more efficient is the DMU; the closer it is to 0, the more inefficient is the DMU. However, the requirement of monotonicity is not respected in the case of joint production of desirable outputs and undesirable outputs, such as, for example, polluting emissions associated with the totality of production processes. In fact, an increase in polluting emissions is associated with a decrease in efficiency, and vice versa.

To take these aspects into account and by growing interest in environmental issues, extensive DEA models have been developed which include the production of undesirable outputs, including, in particular, GHG emissions, with the goal to measure both the environmental and technical efficiency.

In the literature, strategies for incorporating undesirable outputs can be traced back to two types: indirect approaches and direct approaches (Ramli and Munisamy, 2013; Scheel, 2001). The former, widely used since the 1950s, provide for undesirable outputs to be included in traditional DEA models, represented by the CCR and BCC model (where the assumption of constant returns to scale of the CCR model is relaxed) through appropriate transformations. Different studies on the technical efficiency of dairy farms based on traditional DEA models have been conducted (Balcombe et al., 2006; D'Haese et al., 2009; Heinrichs et al., 2013; Larue, 2003; Stokes et al., 2007). Few scholars focus on energy consumption (Hosseinzadeh-Bandbafha et al., 2016) and environmental efficiency of the dairy farm (Berre et al., 2014; Reinhard et al., 2000; Shortall and Barnes, 2013; Toma et al., 2013; Wettemann and Latacz-Lohmann, 2017) (Table 1).

Although indirect approaches have been commonly used in studies aimed at measuring the efficiency of production processes in the presence of undesirable output (Cherchye et al., 2014), they show many limitations.

Firstly, all the indirect approaches are based on radial measurements: that is, every change in output or input takes place according to the same proportions, for each output and input, respectively (Zhao et al., 2014). Most of the time inputs (outputs) do not move proportionally, as in the case of substitute goods. An indirect approach is therefore unable to quantify excesses in individual inputs or the production of bad outputs, and simultaneously the deficit in good output, failing to capture mix inefficiency (Hernández-Sancho et al., 2011).

Secondly, models based on indirect approaches are alternately either input-oriented or output-oriented, while at the same time not permitting to estimate input and output slacks; however, input reduction and output increase must be considered simultaneously.

Thirdly, in indirect approaches, the application of the different types of transformations can strongly affect the results obtained, consequently making it difficult to formulate a sole judgment on the technical efficiency of the production units considered.

Also, radial models reach an efficiency score that does not consider non-radial slacks, which are neglected by the model. Using the efficiency score as the only performance indicator can be misleading if the unconsidered inefficiencies play a significant role in determining the efficiency of DMUs (Cooper et al., 2011).

Finally, another limitation is represented by the relatively low capacity to provide sorting of the DMUs under evaluation (Zhou et al., 2007).

Given these issues, scholars interest has increasingly shifted towards the application of direct, non-radial DEA models, developed in different variants that can be traced back to three types: hyperbolic, directional distance function, and non-radial. The use of the first typology, introduced by Fare et al. (1993), was somewhat limited due to the complexity of resolution of the hyperbolic model.

The non-radial parametric approach of the directional distance function, proposed by Chung et al. (1997) is the most often used. It provides for output expansion at the same time as reduction of inputs by an arbitrarily fixed directional vector, and therefore presents anew the problems already discussed for indirect models (Wei et al., 2012).

The categories of models most often employed in the latest environmental performance studies are non-radial models.

Among the non-radial models, the most widespread approach is the Slack-Based Measures model proposed in its basic version by Tone (2001).

However, the SBM model in its original version does not provide for the inclusion of undesirable outputs. To overcome this limitation, Tone (2004) and Zhou et al. (2006) propose an extended version of the SBM-DEA model to incorporate undesirable outputs.

Due to its features (non-radial and non-oriented model), the undesirable SBM-DEA model allows both input and output slacks to be included simultaneously, without also assuming strictly proportional variations between output and input quantities. Therefore, this model can separately discriminate the level of efficiency or inefficiency for each of the output and input items included.

Table 1
- Overview of reviewed publications on DEA models.

Authors	Year	Field of application	Methodologies applied	Findings
Reinhard, S., Lovell, C. K., & Thijssen, G. J. (2000).	2000	Environmental efficiency estimation for Dutch 613 Dutch dairy farms from 1991 up to 1994.	Stochastic Frontier Analysis (SFA); Data Envelopment Analysis (DEA)	The methodologies applied can estimate environmental efficiency scores although they show strengths and weaknesses. The mean technical and comprehensive environmental efficiency scores differ between the two methods.
Mbaga, M. D., Romain, R., Larue, B., & Lebel, L.	2003	Technical efficiency computation of 1, 143 Québec dairy farms measuring the robustness of the results against three methods.	Cobb-Douglas function; Translogarithmic (TL) Generalized Leontief (GL) function; Data envelopment analysis (DEA)	The functional forms and distributions show a high correlation both in efficiency scores and ranks. Comparisons between these parameters inefficiency scores obtained from parametric estimation and those gained from DEA demonstrate significant discrepancies between the methodologies.
Balcombe, K., Fraser, I., & Kim, J. H.	2006	Technical efficiency (TE) evaluation for 241 Australian dairy farms under different frontier methodologies	Bayesian and Classical stochastic frontiers; Data Envelopment Analysis (DEA)	Identification of statistical differences between the point estimates of technical efficiency arises by the different methodologies applied. The estimation technique used in the study does not statistically affect the rank of farm level technical efficiency.
Zhou, P., Ang, B. W., & Poh, K. L.	2006	Modelling CO2 emissions of 30 OECD countries from 1998 to 2002	Extended SBM-DEA model to incorporate undesirable outputs	Applying two different SBM efficiency measure for modelling environmental scenario, the authors find two different measures. The composite index can strongly discriminate the economic and environmental performance. The other measure allows estimating regulation impact at the environmental level.
Stokes, J. R., Tozer, P. R., & Hyde, J.	2007	Calculation of efficiency for 34 Pennsylvania dairy farms to determine all the factors used to be efficient at the production and economic level	Data Envelopment Analysis (DEA)	Applying the DEA method lead to identifying the inefficient producers that can take efficient producers as an example to come through more significant levels of efficiency. It should not be achieved the highest level of production, but different resources should be aggregated to reach an efficient level of production that could be less than the maximum production level.
D'Haese, M., Speelman, S., Alary, V., Tillard, E., & D'Haese, L.	2009	Efficiency level computation in milk production for 34 Dairy farms in Reunion Island (India)	Data Envelopment Analysis (DEA) with subvectors efficiency estimation on specific input (Land)	The technical efficiencies estimated with DEA model is higher than the average subvector (land) efficiencies. The efficient producers show both a higher milk production and milk production per cow as well as higher land availability compared with those less efficient. To better tackle, the inefficient use of land, milk production based on land ratio should be promoted by policy.
Iribarren, D., Hospido, A., Moreira, M. T., & Feijoo, G.	2011	Eco-efficiency assessment and economic benefits of 72 Farms in Galicia (NW Spain)	Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA)	The LCA-DEA integration can lead to finding good estimations of operational and environmental parameters at the dairy farm level. Using LCA-DEA combined allow to bypass standard deviation concerns, identify the most efficient producers as well as determine both economic savings and eco-efficiency evidence. Generally, for its characteristics, it could support decision making in the farms and inform policymaker about environmental reference values.
Li, L. B., & Hu, J. L.	2012	Ecological total-factor energy efficiency (ETFEE) of 30 regions (China) (2005–2009)	Slack-based measure(SBM) with undesirable outputs	The authors find a low performance of ETFEE index at regional level and it decreases when emissions are considered. A positive relationship between ETFEE and GDP per capita is found as well as large differences for the ETFEE among the provinces have been estimated.
Choi, Y., Zhang, N., & Zhou, P.	2012	CO2 emissions in different provinces of China (2001–2010)	Slacks-based DEA model (SBM-DEA)	Analysing the reduction potential, efficiency, and abatement cost of CO2 emissions in China, the authors, find that provinces emission across the nation is unbalanced. Although CO2 emission reduction can reach a high level on average, China is still carbon inefficient. Being a young nation only recently involved into the stage of emission abatement, the authors suggest considering a lower market pricing system by setting itself in the context of the international ETS transactions.
Wei, C., Ni, J., & Du, L.	2012	CO2 abatement in 29 provinces of China (1995–2007)	Extended Slacks-Based Measure (SBM) with undesirable outputs	Applying an extended Slacks-Based Measure (SBM) model with the undesirable output, the authors formulate a CO2 Abatement Capacity Index (ACI). According to the index, there is a discrepancy across the provinces both in potential reduction capability and marginal abatement cost

(*continued on next page*)

Table 1 (*continued*)

Authors	Year	Field of application	Methodologies applied	Findings
				due to industry structures, energy compositions and their participation in the trade market.
Heinrichs, A. J., Jones, C. M., Gray, S. M., Heinrichs, P. A., Cornelisse, S. A., & Goodling, R. C.	2013	Determining the costs to raise dairy heifers to identify the most efficiently farms that use (major) inputs to produce potentially profitable dairy heifers (Pennsylvania)	Data Envelopment Analysis (DEA)	Applying the DEA model, the authors find that combination of feed and labour investment are better in 9 farms out of 44. Findings highlight how efficiency is reached by cattle management systems that employ the minimum input costs. Also, efficiency could be reached by higher input costs system using younger cattle that produce more milk comparing to the rest of the livestock.
Shortall, O. K., & Barnes, A. P.	2013	Technical and environmental efficiency of dairy farms with respect to GHG emission (Scotland)	Data Envelopment Analysis (DEA)	Farms, showing a large dimension and a higher harvest, are more efficient both at a technical and environmental level. The authors suggest Scottish dairy system could improve competitiveness decreasing GHG emissions by increasing efficiency, highlighting how the environmental benefits achieved depends on how efficiency is increased.
Toma, L., March, M., Stott, A. W., & Roberts, D. J.	2013	Comparing the environmental efficiency of pastures system across 2 genetic lines of Holstein-Friesian to evaluate both any interaction between genotype and environment and livestock environmental impact (Scotland)	Data Envelopment Analysis (DEA)	According to the authors, no interaction between genotype and environment has been detected across the two genetic lines. Pollutants used as inputs in the model as well as cattle health unstable are essential when the environmental efficiency of the pastures system is measured.
Chang, Y. T., Zhang, N., Danao, D., & Zhang, N.	2013	Analysis of China's environmental efficiency in transportation sector	SBM-DEA model with undesirable output	Applying a non-radial SMB-DEA model, the authors computed CO2 emissions. Many of the China's provinces have found to be environmentally inefficient at the transportation industry level.
Song, M., Wang, S., & Liu, Q.	2013	Review of environmental efficiency computation models	Improved SBM-DEA model (ISBM-DEA) compared with classic SBM	Comparing the improved and the classical SBM-DEA model, the ISBM accounts for the effect of undesirable output on production efficiency compared with the classical model. The results imply the improved model could be applied mainly in different fields.
Song, M., & Guan, Y.	2014	Environmental efficiency valuation of a demonstration area in Wanjiang city cluster (China)	Super efficiency Slacks-based Measure (SBM) with Bayesian statistical methods to small sample	Heterogenous performances in terms of environmental efficiency among the 31 provinces are estimated. In addition, the percentage weight of secondary industry on GDP and the import and export's share in GDP positively affect environmental efficiency, which is decreased by per capita GDP, conversely.
Berre, D., Blancard, S., Boussemart, J. P., Leleu, H., & Tillard, E.	2014	Trade-off between milk production and its environmental impact on greenhouse gas (GHG) emissions and nitrogen surplus in a high input tropical system.	Data Envelopment Analysis (DEA) with undesirable outputs and the directional distance function	Among the forth scenarios identified by the authors, the sustainable intensification is that best of all may generate results pointing out a decreasing in CO2 emission per litre of milk produced and an increase in milk production for each kg of nitrogen surplus. According to the authors, the Data Envelopment Analysis is a very flexible method able not only to evaluate many eco-inefficiency reduction policies but also to analyse the agronomic, economic and environmental issues globally.
Chen, S.	2015	Evaluation of the ecological economic transition and development in 31 Chinese provinces from 1981 up to 2012.	Slacks-based Measure (SBM)	China provinces have faced across time fluctuating perfoemances about the economic ecological transition measured as the ratio between the ecological TFP growth on GDP growth. However, the ratio show a more stable trend at national level.
Hosseinzadeh-Bandbafha, H., Safarzadeh, D., Ahmadi, E., & Nabavi-Pelesaraei, A.	2016	Computation of energy efficiency and optimum energy consumption in dairy farms in Qazvin city (Iran)	Data Envelopment Analysis (DEA)	According to the authors, the most use of energy in dairy farming relies on feed and fossil fuel. Reduction in energy consumption could be achieved by managing feed intake that is the primary step affecting the possible GHG emission reduction linked to enteric fermentation. Also, implementing new models, namely genetic algorithms, could optimise milk production. In general, it seems that farmers can achieve a sustainable agriculture optimising energy consumption which in turns could lead to a decrease in the product price.
Deng, G., Li, L., & Song, Y.	2016	Estimation of water use efficiency in China from 2004 up to 2013 considering domestic sewage produced in 31 provinces.	SBM-DEA model	The authors find that higher is the econimic development of the provinces and higher is water efficiency. In addition, the efficiency of the capital

Table 1 (*continued*)

Authors	Year	Field of application	Methodologies applied	Findings
				input is higher than labour and water used. Water use efficiency depends on weight percentage of the added value of agricultural sector, on water usage per capita, and sewage emissions per unit of output.
Li, T., Baležentis, T., Makutėnienė, D., Streimikiene, D., & Kriščiukaitienė, I.	2016	Determination of the fundamental factors linked to energy CO2 emissions across agricultural sectors of European countries	SBM-DEA model	Evaluating the primary factors of CO2 emission, the environmental efficiency and shadow prices in 18 countries, the authors find that reduction in energy intensity implies a fall in the CO2 emissions. The north European countries have the lowest carbon shadow prices entailing, at a policy level, that increase efficiency in energy use is preferable than a fuel mix adoption.
Wettemann, P. J. C., & Latacz-Lohmann, U.	2017	Analysis of the trade-offs between a cost-efficient and a GHG-efficient production for 216 dairy farms in northern Germany.	Data Envelopment Analysis (DEA)	The results of the trade-offs between a cost-efficient and a GHG-efficient production in the dairy sector show that farms under investigation are more GHG-efficient than cost-efficient. Those dairy farms efficient on average both economically and environmentally show a higher share of legumes and a rise in the cows' average lifespan.

Recently, many studies have used the SBM model with undesirable output to investigate water (Chen, 2015; Deng et al., 2016; Song and Guan, 2014), energy (Li and Hu, 2012) and environmental efficiency (Chang et al., 2013; Choi et al., 2012; Song et al., 2013; Wei et al., 2012; Zhou et al., 2006) as well as to estimate the shadow price of CO_2 emissions (Choi et al., 2012; Li et al., 2016) (Table 1). As far as it is known, only one study (Iribarren et al., 2011) has integrated an input-oriented SBM-DEA model with the LCA methodology to estimate the efficiency of Spanish dairy cattle farms in terms of CO_2-eq, the latter considered as undesirable output associated with milk production (Table 1). Yet, the environmental efficiency of the dairy sector under the SBM model has been widely neglected. In addition, none of the studies have used the above mention model to estimate environmental efficiency and shadow prices for GHG emissions in the sector. This research tries to partially fill the gaps found in existing literature by focusing its analyses on the evaluation of the interrelationship between the efficiency of the dairy sector Greenhouse Gas (GHG) emissions and CO_2 reduction costs.

Given the above, according to Tone (2004), Cooper et al. (2007) and Iribarren et al. (2011), the non-parametric, non-radial and non-oriented approach of SBM-DEA is adopted. The model is integrated with the results of the LCA of ten dairy cattle farms in Umbria (Italy) published in Cecchini et al. (2016), to estimate the environmental efficiency and CO_2 emission abatement potential by incorporating the corresponding slack variables. Also, the dual model of the SBM-DEA will be used to quantify the marginal CO_2 reduction costs.

2. Method and data

The analysis considers CO_2-eq emissions, calculated using the LCA method in Cecchini et al. (2016), as undesirable output, whereas labour, feed supply, capital, utilised agricultural area used for livestock activities, and livestock units constitute the inputs of the production process. Milk, which is most of the gross marketable production of dairy farms, represents the only desirable output considered in the analysis.

The SBM-DEA is applied with a twofold objective: 1) determine the farm environmental efficiency, together with the quantification of the CO_2 abatement potential; 2) determine the shadow price of CO_2 and the opportunity costs associated with the emission of pollutants (e.g. Deng et al., 2016; Wei et al., 2012; Zhou et al., 2007).

These goals are integrated into this work. The study aims to build the efficiency frontier of the farms throughout the primal model of SBM-DEA and to calculate for each case study, the efficiency scores. The inclusion of a dedicated slack variable in the model will permit at the same time to estimate the potential for undesirable output abatement, achievable by inefficient farms to reach the efficiency frontier. The measurement of the distance of each farm from the frontier will also allow for the quantification of the attainable improvements for each input or bad output, in terms of possible reductions, and good output, in terms of possible increases. The second objective will be pursued with the dual model of SBM-DEA, which will be adopted in the second phase to estimate the shadow price of CO_2-eq emissions. Marginal abatement costs knowledge will also allow to assess the economic impact of any farms strategies aimed at reducing polluting emissions, as well as the introduction of possible incentive mechanisms by public decision makers.

2.1. The SBM (slack-based measure) model with undesirable output

The efficiency measure obtained by SBM-DEA model satisfies the following properties (Cooper et al., 2007): i) it does not vary with the unit of measurement with which inputs and outputs are set (this property is defined as unit invariant or dimension free); ii) it is a decreasing and monotone on each slack and slack input; iii) Reference-set dependent: it is determined solely for the DMU set considered in the analysis.

The SBM model has three different variants, i.e. input-, output- and non-orientation. The non-oriented model adopted in this study incorporates both input and output-oriented models, allowing estimation, at the same time, of input excesses and output deficits (slack variables).

Assuming that the DMUs set is k = {1,2, …, K}, where each DMU has I inputs, J good outputs and L bad outputs, the analysis considered the following three vectors, respectively for inputs, good outputs and bad outputs for the k_{th} DMU: $x = (x_1, x_2, \ldots, x_I) \varepsilon \Re^I_+, y^g = (y^g_1, y^g_2, \ldots, y^g_J) \varepsilon \Re^J_+$, $y^b = (y^b_1, y^b_2, \ldots, y^b_J) \varepsilon \Re^L_+$.

Consequently, the production possibility set (P), assuming constant scale returns (CRS), can thus be indicated Eq. (1):

$$P = \left\{ \left(x, y^g, y^b\right) | x \geq \sum_{k=1}^{K} \lambda_k x_k, y^g \leq \sum_{k=1}^{K} \lambda_k y^g_k, y^b \geq \sum_{k=1}^{K} \lambda_k y^b_k, \lambda_k \geq 0 \right\} \tag{1}$$

where $\lambda_k$is an intensity variable.

The CRS assumption is justified by the farms operate in a competitive environment (Lozano et al., 2009) and a high degree of flexibility for the different production technologies; In addition, the CRSs have, with respect to VRSs (variable returns to scales), more significant discrimination skills (Zhou and Ang, 2008).

The non-oriented SBM-DEA model with undesirable outputs (Cooper et al., 2007; Tone, 2004)) is used in this work to measure efficiency It is indicated by ρ_o^* of DMU_o under evaluation $(x_o y_o^g, y_o^b)$ (where $o = 1, \ldots, K$) and provides for minimization of the following fractional objective function, which implies, therefore, the maximization of slack variables s_i^x, s_j^g, s_l^b (Eq. (2))

$$\rho_o^* = \min \frac{1 - \frac{1}{I}\sum_{i=1}^{I}\frac{s_i^x}{x_{io}}}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J}\frac{s_j^g}{y_{jo}} + \sum_{l=1}^{L}\frac{s_l^b}{y_{lo}}\right)}$$

s.t.

$$x_{io} = \sum_{k=1}^{n}\lambda_k x_{ik} - s_i^x, i = 1,2,\ldots,I;$$

$$y_{jo}^g = \sum_{k=1}^{n}\lambda_k y_{jk}^g - s_j^g, j = 1,2,\ldots,J;$$

$$y_{lo}^b = \sum_{k=1}^{n}\lambda_k y_{lk}^b + s_l^b, l = 1,2,\ldots,L;$$

$$\lambda_j \geq 0, s_i^x \geq 0, s_j^g \geq 0, s_l^b \geq 0 \tag{2}$$

where $\rho_o^*, s_i^x, s_j^g, s_l^b$ are respectively the efficiency score, excess input, good output deficit and excess of bad output, and the DMU_o is defined as efficient in the presence of CO_2-eq emissions - when $\rho_o^* = 1$and $s_i^x = s_j^g = s_l^b = 0$ consequently. The objective function is normalised, allowing for comparison of the efficiency scores between the observations. In addition, it can be observed that the bad output, despite not being transferred, is treated as input in the constraints but is treated as output in the objective function where it is located at the denominator. The model is constant returns as it has no negative data and has no data transfer (Cooper et al., 2007).

The objective function value meets the following condition $0 \leq \rho_o^* \leq 1$, and it is sharply decreasing in s_i^x, s_j^g, s_l^b If the score is less than 1, the farm is inefficient and can project itself on the efficient frontier this way Eq. (3):

$$x_{io} - s_i^{x*} \rightarrow x_{io}^*$$

$$y_{jo}^g + s_j^{g*} \rightarrow y_{jo}^{g*}$$

$$y_{lo}^b - s_l^{b*} \rightarrow y_{lo}^{b*} \tag{3}$$

Values x_{io}^* , y_{jo}^{g*}, y_{lo}^{b*}, describe the point on the efficient frontier achievable by the DMU considered by eliminating excess input and bad output and increasing good output deficits, based on the optimal solution for slack variables obtained from the SBM model.

2.2. Estimation of CO_2-eq abatement potential, increase of milk production and reduction of inputs

Regarding CO_2-eq emissions, in case of inefficiency of the DMU_o, there will be a positive value of the slack variable s_l^b associated with it, representing the excess production of polluting emissions that the DMU_o has to reduce to become eco-efficient. As a result, this value will also be equal to the CO_2 abatement potential (PA_o) that can be achieved by the DMU_o in question Eq. (4):

$$PA_o = s_l^b \tag{4}$$

In line with what Hu and Wang (2005) proposed, the efficiency of undesirable output (UOE_o) can be calculated as the ratio between the emission level to be reached and the current level (Chang et al., 2013; Fukuyama and Weber William, 2009) Eq. (5):

$$UOE_o = \frac{y_{lo}^b - s_l^{b*}}{y_{lo}^b} \tag{5}$$

Likewise, the efficiency of production of desirable output (DOE_o) and the individual inputs (IE_o) can be determined, respectively, as (Eqs. (6) and (7)):

$$DOE_o = \frac{y_{jo}^g - s_j^{g*}}{y_{jo}^g} \tag{6}$$

$$IE_o = \frac{x_{io} - s_i^{x*}}{x_{io}} \forall\ i \in I \tag{7}$$

The values of UOE_o, DOE_o, and IE_o are between 0 and 1. The higher the value, the higher the efficiency level is, and consequently the reduction or increase potential for undesirable outputs/inputs and desirable outputs is lower (Hu and Kao, 2007; Wei et al., 2012).

In any case, the presence of a CE value of 1 does not imply that DMU_k cannot achieve absolute improvement in the environmental efficiency of its production activity but attests relative efficiency with respect to the sample of observations considered (Wei et al., 2012).

2.3. Estimation of the marginal cost of CO_2-eq

To estimating the shadow price of undesirable outputs, it was decided to use the dual model of equation (2) proposed by Tone (2004) and adopted, for example, by Choi et al. (2012) and Li et al. (2016). After linearization, the dual model of Eq. (2) can be expressed by the following expression Eq. (8):

$$\max \sum_{j=1}^{J} p_j^g y_{jo}^g - \sum_{i=1}^{I} p_i^x x_{io} - \sum_{l=1}^{L} p_l^b y_{lo}^b$$

s.t.

$$\sum_{j=1}^{J} p_j^g y_{jk}^g - \sum_{i=1}^{I} p_i^x x_{ik} - \sum_{l=1}^{L} p_l^b y_{lk}^b \leq 0, k = 1,2,\ldots,K;$$

$$p_i^x \geq \frac{1}{I}\left[\frac{1}{x_{io}}\right], i = 1,2,\ldots,I;$$

$$p_j^g \geq \frac{1 + \sum_{j=1}^{J} p_j^g y_{jo}^g - \sum_{i=1}^{I} p_i^x x_{io} - \sum_{l=1}^{L} p_l^b y_{lo}^b}{J+L}\left[\frac{1}{y_{jo}^g}\right]$$

$$p_l^b \geq \frac{1 + \sum_{j=1}^{J} p_j^g y_{jo}^g - \sum_{i=1}^{I} p_i^x x_{io} - \sum_{l=1}^{L} p_l^b y_{lo}^b}{J+L}\left[\frac{1}{y_{lo}^b}\right] \tag{8}$$

where the vectors of dual variables p_i^x, p_j^g e p_l^b, represent the input of shadow prices, desirable output (milk) and undesirable output

(CO_2-eq emissions) respectively. The optimal prices found ensure that the optimized profit value is at most equal to 0 for the efficient DMU. Positive profits are therefore not possible for each DMU considered. The last three constraints ensure that double variables have a positive sign Tone (2004).

Assuming the market price of desirable output (i.e. milk) is equal to its absolute shadow price, it is possible to express the shadow price of CO_2-eq ($SP_{CO2\text{-}eq}$) (Wei et al., 2012; Fare et al., 1993; Lee et al., 2002) with the following expression (Eq. (9):

$$SP_{CO2-eq} = 400\text{€} \cdot \frac{p_l^b}{p_j^g} \tag{9}$$

where € 400 is the average market price of milk (€/ton) in the year 2014 in Umbria. The shadow price SP_{CO2}, which represents the trade-off between CO_2-eq emissions and milk produced, also constitutes the marginal cost of CO_2-eq (Du et al., 2015; Lee, 2005; Wei et al., 2012). Marginal abatement costs were subsequently compared with the market prices of carbon credits to assess the business benefits of possible mitigation measures of GHG emissions.

All the models described were implemented and solved in the General Algebraic Modelling System (GAMS) environment.

2.4. Data collection

The study of environmental efficiency, CO_2-eq abatement potential and marginal abatement costs were implemented in 10 dairy farms located in the district of Perugia in the Umbria Region in 2014.

The selection of dairy farms was based on a dimensional criterion concerning livestock unit (LSU), to ensure a representative sample with respect to the population of Umbrian farms. Based on dairy sector ISTAT data (ISTAT, 2010) collected in Umbria, the following three main business size categories were identified: Class 1 (0–99 LSU); class 2 (100–199 LSU); class 3 (200–299 LSU); class 4 (300 or more LSUs). The study considered two farms for each of the classes 1 and 2, four for class 3, and 2 for class 4. The 10 case studies were selected based on the availability of the farms involved to provide the information needed to implement the proposed SBM-DEA model and represent a representative sample of Umbrian dairy farms.

The dataset[1] covered primary technical, economic and financial evidence that were gathered by the surveys on the farms, consultation of management software and computer registers, as well as available paperwork, including field and cattle shed stock books or registers, waybills delivery, and invoices.

Taking as a time horizon a year, the model considered five main inputs: livestock units (LSU), labour, feed supply externally procured, utilised agricultural area used for feeding livestock, capital stock. The only desirable output included in the study is milk production, while CO_2-eq emissions associated with the entire production process were treated as undesirable output.

Below, a detailed description of each input and output entry is reported.

Livestock units. This input was used to measure the size of the herd. It helped to obtain an equivalent and single measure that considered the number of all the homogeneous types of dairy cows raised in the farm, not only the lactating cows directly related to the production of milk.

Labour. The workforce was quantified as the total number of hours spent by family workers and dependent workers, both permanent and temporary, involved in each operation related to dairy farm activity.

Feed supply. This input referred to the total quantity, as kg of dry matter of fodder and concentrate purchased on the market, administered to the different homogeneous types of livestock.

Utilised Agricultural Area. This input included all areas allocated for productions reused in dairy farm activities (pasture, silage crops and forage crops).

Capital stock. It was determined as the present value of tangible fixed assets (buildings, equipment and facilities) and was derived from the financial statements available at farms level.

Milk production. The amount of milk produced by each farm was the only indicator used to estimate desirable output as reported before. In fact, milk production has been shown to be the activity with the most significant weight (in percentage) of the gross farm sales, where other businesses (sales of meat or by-products) contribute to some slight and negligible extent.

CO_2-eq emissions. The CO_2-eq emissions of each farm were considered undesirable output. The values, expressed in terms of Carbon Footprint (CF) associated with the milk production, were calculated using a “cradle to gate” LCA analysis reported in Cecchini et al. (2016).[2] The same approach was used to expand the sample and increase the external validity of the analysis to the other five dairy farms in the Umbria Region (Italy), according to the SBM-DEA methodology.

3. Results and discussion

3.1. Descriptive statistics

Compared to outputs, the 10 dairy farms had an average output value (milk) of 1479.67 tons, while the undesirable output (CO_2-eq emissions) was 1929.44 tons of CO_2-eq (Table 2). Both outputs presented high variability among the farms considered, as they showed the magnitude of the min-max range and the standard deviation values. Regarding inputs, the average size of the herd is 252 LSU, with a minimum of 68 LSUs for the smallest farm, up to a maximum of 578 LSU for the most extensive farm. Regarding work, on average, sample farms employed about 8632.64 h for livestock activity, with differences between farms related to herd size, stall management, and stall shape. About concentrates and silage purchases, the average quantity was 698.83 tons of dry matter and varies between 81.52 and 1.451.35 tons depending on the LSU number of the farm. The utilised agricultural area and the capital stock were, on average, 121 ha and 1.35 Million Euro respectively, with high variability within the sample.

3.2. Input/output efficiency and CO2-eq emission potential reduction

Tables 3 and 4 include, respectively, in aggregate form and by the single farm, SBM Efficiency scores, estimated under equation (2), and the efficiency scores calculated for each input, desirable output and undesirable output, respectively according to equations (5), (6) and (7). At the same time, in Tables 5 and 6, respectively, in aggregate form and by the single farm, the input and output slacks values are reported in the respective units of measure, which represent the excess inputs and bad outputs and the good output deficits preventing the farm from reaching the efficient frontier. In

[1] The authors will pleased to share the data set in Excel format contacting the corresponding author by e-mail.

[2] Reference is reported for details and insights on the methodology and results obtained with respect to five of the case studies here considered.

Table 2
– Descriptive statistics of the input and output variables of the sample (N = 10).

Inputs/outputs	Variable	Unit	Min	Max	Mean	Standard Deviation
Desiderable output	Milk	tons	265.33	3363.56	1479.67	920.95
Undesirable output	CO_2-eq	tons	241.45	3975.00	1929.44	1098.76
Input	Livestock Unit	LSU	62.00	578.00	252.34	155.09
Input	Labour	hours	3672.00	14,782.50	8632.64	3310.95
Input	Feed	tons of dry matter	81.52	1.451.35	698.83	487.78
Input	Utilised agricultural area	ha	39.30	293.80	120.99	84.62
Input	Capital stock	million Euros	0.55	2.75	1.35	0.76

Table 3
SBM efficiency, input and output efficiency of the sample (N = 10).

Variable		Min	Max	Mean	Standard Deviation
SBM Efficiency		0.52	1.00	0.83	0.21
Input efficiency	Livestock Unit	0.62	1.00	0.931	0.126
	Labour	0.31	1.00	0.827	0.245
	Feed	0.57	1.00	0.926	0.127
	Utilised agricultural area	0.31	1.00	0.857	0.250
	Capital	0.34	1.00	0.801	0.282
Desiderable output efficiency	Milk	1.00	1.00	1.000	0.000
Undesirable output efficiency	CO_2-eq emission	0.49	1.00	0.850	0.199

the case of bad output (CO_2-eq emission), this value corresponds to the abatement potential in terms of tons of CO_2-eq. According to Li et al. (2016), however, the SBM efficiency scores, being calculated by considering input and output slack simultaneously, are not easy to interpret, although they provide an indication of overall efficiency and are obviously correlated negatively with the inputs and slack output. Therefore, below, the authors mainly focus on the results obtained for efficiency scores broken down into inputs, CO_2-eq emissions and milk production.

According to Table 3, high levels of productive performance are noted, as shown by the SBM average efficiency score of 0.83.

Given the average efficiency scores for individual inputs, the farms being examined are particularly efficient about the use of LSU (0.931) and feed (0.926) factors, demonstrating how productivity and management of feeding have reached high standards in Umbria dairy herds. More uneven is the situation when the other three inputs are considered, with substantially lower average efficiency scores, respectively 0.827 for Labour, 0.857 for Utilised Agricultural Area, and 0.801 for Capital. Referring to these inputs, sample farms show possible reductions in the employ ranging from 14.3% to 20%, which can be achieved by projecting inefficient farms towards the efficient production frontier.

Regarding milk production, the desirable output efficiency average assumes a value of 1, meaning that all sample farms have achieved full efficiency. By contrast, concerning CO_2-eq emission efficiency, the results show that the 10 farms in the sample have an average value of 0.85, which implies an average potential for reducing CO_2-eq of 15% in the case of those farms with inefficient CO_2-eq emissions reaching those operating along the efficient frontier. In aggregate terms, the abatement potential of the 10 farms considered is high and equal to 3808.65 tons of CO_2-eq, demonstrating how the Umbrian dairy sector, despite significant improvements in recent years, still has large margins for increasing its environmental performance.

By analysing the results for a single farm, Table 4 shows that, in 2014, 6 dairy farms out of 10, have the maximum SBM efficiency score, equal to 1, indicating the achievement of full efficiency, both in terms of desirable and undesirable inputs and outputs. These farms are therefore positioned along the efficient frontier, as demonstrated by the null values of inputs and output slacks (Table 6), and have no margins to improve their performances, neither by reducing inputs or CO_2-eq nor through the increase in milk production. Farms 2, 4, 5, 7, 8 and 10 are the benchmark against which the relative efficiency of other farms is calculated.

The remaining 5 farms, on the other hand, have SBM efficiency scores lower than the unit, demonstrating how their production processes are not entirely efficient due to excess inputs and CO_2-eq production (Table 5).

Focusing on input efficiency, 3 farms out of 4 with SBM efficiency score less than 1 are not efficient in the use of Livestock Units, with efficiency index values ranging from 0.623 to 0.846, with reduction margins that range from 37.7% to 15.4%. This result

Table 4
SBM Efficiency, input and output efficiency of the ten analyzed dairy farms.

Farm	SBM Efficiency	Input efficiency					Desiderable output efficiency	Undesirable output efficiency
		Livestock Unit	Labour	Feed	Utilesed agricultural area	Capital	Milk	CO_2-eq emission
1	0.52	0.842	0.702	1.000	0.320	0.303	1.000	0.543
2	1.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3	0.52	0.846	0.314	0.863	0.494	0.410	1.000	0.737
4	1.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5	1.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000
6	0.59	0.623	0.607	0.687	0.784	0.770	1.000	0.628
7	1.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000
8	1.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000
9	0.64	1.000	0.646	0.711	0.975	0.528	1.000	0.595
10	1.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 5
Input and output slacks of the sample (N = 10).

Variable		Min	Max	Mean	Standard Deviation
Input slacks	Livestock Unit	0.00	106.70	16.14	34.32
	Labour	0.00	5227.41	1746.01	2372.07
	Feed	0.00	419.94	68.45	143.12
	Utilised agricultural area	0.00	199.66	25.25	62.09
	Capital	0.00	1.63	0.37	0.61
Good output slack	Milk	0.00	0.00	0.00	0.00
Undesirable output slack	CO_2-eq emission	0.00	1608.12	380.86	600.00

Table 6
Input and undesirable output potential redundancy and marginal abatement costs of CO_2-eq emissions of the ten analyzed dairy farms.

Farm	Input redundancy					Good output deficiency	Undesirable output redundancy	Abatement costs	
	Livestock Unit	Labour (hours)	Feed (tons of dry matter)	Utilised agricultural area (ha)	Capital (million Euros)	Milk (liters)	CO_2-eq emission (tons)	(€/ton of CO_2-eq)	*t*-test
1	40.12	2480.63	0.00	199.66	1.63	0.00	1119.74	217.14	−0.32
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	327.75	1.03
3	14.54	4658.14	32.62	21.19	0.65	0.00	175.22	297.09	0.66
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	111.55	−1.61
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	337.25	1.15
6	106.70	5093.94	231.95	27.05	0.16	0.00	905.57	228.00	−0.18
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	334.88	1.12
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	202.67	−0.49
9	0.00	5227.41	419.94	4.56	1.30	0.00	1608.12	212.80	−0.37
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	161.72	−0.99
Total	**161.36**	**17,460.12**	**684.50**	**252.46**	**3.73**	**0.00**	**3808.65**		
Mean								243.08	
Standard Deviation								78.00	

is mainly due to the differences in genetics, health management and fecundation, which significantly affect productivity. In relation to the use of the labour factor, all non-SBM efficient farms present an excess of this element. As showed by the efficiency values related to it, they are particularly low in the case of farm 3 (0.314), followed by farm 6 (0.607), farm 9 (0.646), and farm 1 (0.702). The exclusion of such inefficiencies would result in the considerable reductions in associated labour costs, estimated at a range ranging from 68.6% to about 30%.

As far as feed is concerned, 7 out of 10 farms are located along the efficient frontier, while farms 3, 6 and 9 show significant efficiency margins of 13.70%, 31.13% and 28.9%, respectively. This result shows how though more than two-thirds of the farms have efficient feed management. This aspect is still critical in 30% of the cases, which would require main improvements, with significant benefits for profitability. However, high variability among farms with SBM efficiency score <1 is related to the land use efficiency, with values between 0.320 in case of farm 1 and 0.975 in farm 9. The main differences affecting this result are the differences in the type of agronomic management practised, the degree of intensification of the production process and the geo-pedological characteristics of the cultivated land. Also, regarding equity capital investment, farm 1 is the least performing (0.303), followed by 3 (0.410), 9 (0.528) and 6 (0.770). Therefore, in case of projection on the efficient frontier, the potential reduction margins are high. These results would allow lower jobs estimated from 69.7% (farm 1) to 23% (farm 6). However, such reductions would only be achieved in a long-term perspective, given the fixed nature of the invested capital considered in the study. Compared to the enormous output, the data show that all non-SBM efficient farms present environmental performance deficits with CO_2-eq efficiency values between 0.543 and 0.737. In absolute terms (Table 5), farm 9 shows the highest abatement potential in terms of tons of CO_2-eq (1608.12) followed by farm 1 (1119.74), farm 6 (905.57) and farm 3 (175.22). In percentage terms, farm 1 has the highest reduction potential (45.7%), followed by farm 9 (40.5%), farm 6 (37.2%), farm 3 (26.3%). These results are higher than those quantified by a DEA model based on the Shepard distance function, by Wettemann and Latacz-Lohmann (2017). In fact, they have estimated a total emission reduction potential for German dairy farms ranging from 4.5% to 11.9%. Our results are compatible with those obtained by Iribarren et al. (2011) by studying the environmental efficiency of Spanish dairy farms. The authors estimated through an input-oriented SBM-DEA model, a potential average impact reduction of the Global Warming Potential (GWP) equals to 23%. Overall, the estimated abatement potential also has important policy implications. Findings highlight that consistent CO_2-eq savings could be achieved together with an increase in the technical efficiency of the milk production processes, if all the farms will operate on the production frontier. Win-win scenario in environment and economic outcomes production are possible and should be promoted by policy measures in a local and global perspective.

3.3. CO_2-eq shadow price

Following equations. (8) and (9), for the 10 dairy farms considered, the shadow price of CO_2-eq emissions was determined, representing the trade-off between desirable and undesirable output. Shadow prices represent the cost of reducing harmful emissions and can be interpreted as marginal abatement costs, expressed in €/ton of CO_2-eq, which must be sustained by farms to improve their environmental performance. Table 5 shows the 10 dairy farms in the sample have to spend on average € 243.08 in terms of lower milk production per ton of CO_2-eq reduced. A two-tailed *t-test* was carried out by comparing the average abatement cost calculated for each farm and the one calculated for the overall sample (Table 5).

For each observation, the absolute value of *t-test* statistic does not exceed the critical values of the T-distribution for a confidence level of $\alpha = 0.05$ and 9 degrees of freedom ($t_{0.975,9=}2.262$). Thus, the null hypothesis of no differences between the single farm and the whole sample abatement costs is accepted.

However, there is a high degree of variability among the farms in the sample: the most significant cost reduction concerns farm 5 (337.25 €/ton) while the minimum, about three times lower, is in farm 4 (111.55 €/ton). These results show that a regional standard for CO_2-eq emissions in dairy farms has not yet been achieved.

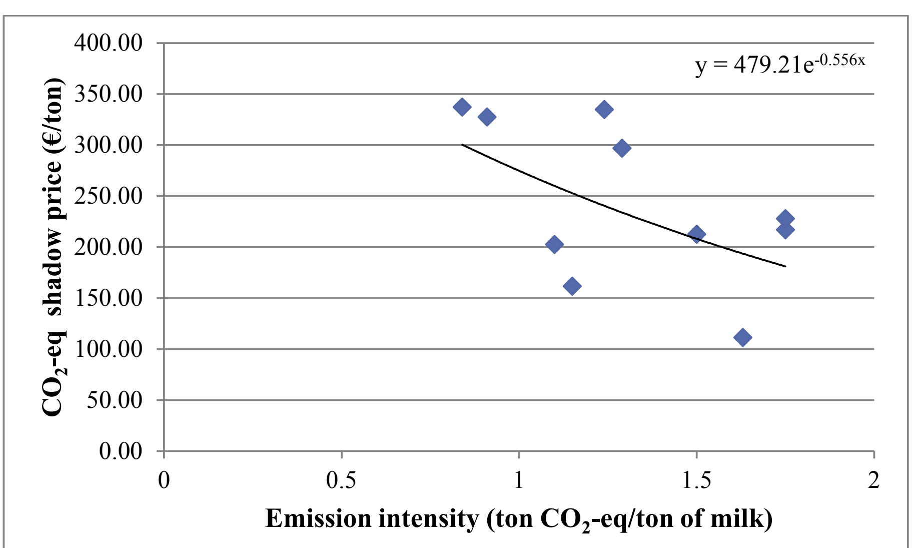
These findings could also support the action of policy makers in their decisions, which need a general overview of environmental performance of the dairy livestock sector, rather than being interested in single farms' performances.

More specifically, the quantification of the CO_2-eq abatement costs could represent a basic reference for public authorities to design a cost-effective policy to support improvements incentive-based measures (Oates, 1992; Stavins, 2010).

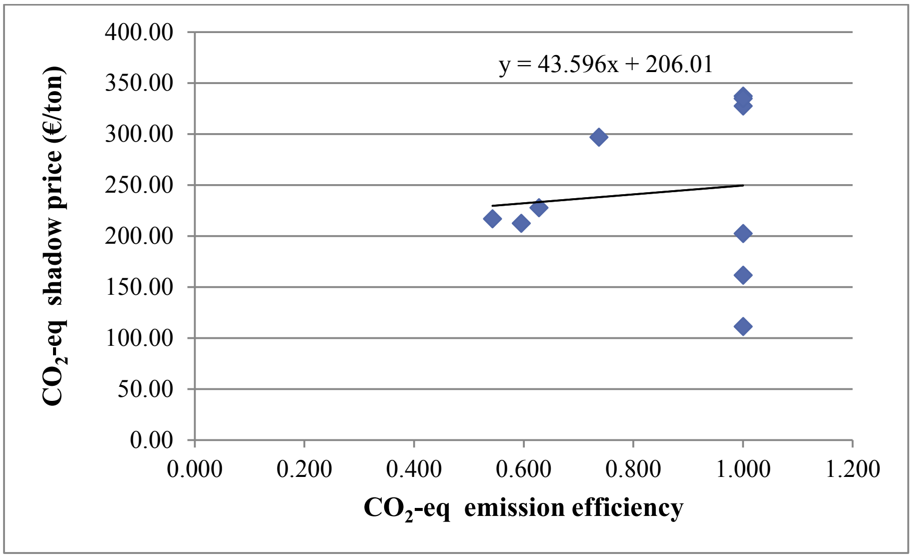
The incentive-based instruments could be divided in price-based and quantity-based measures (Weitzman, 1974). The former dealing with the introduction of a CO_2 tax, while the latter are mainly represented by Emission trading system (ETS) (Kesicki, 2010). In both of these instruments a price for the emission of CO_2 is provided, thus encouraging producers to reduce their environmental impact. In the first case, the knowing of the marginal abatement cost allows for the quantification of the reduction amount achievable by introducing a CO_2 tax at different levels. As matter of fact, all the reductions that can be carried out by farms with costs up to the CO_2 tax will be realized. Otherwise, farms prefer to pay rather than adapt, to the detriment of the effectiveness of the measure.

Conversely, in an ETS an overall target level of pollution is established, and the related emission allowances are allocated among firms in the form of credits. Such a competitive CO_2 allowances market framework would allow the farm with a high shadow price to become a buyer in the emission trading market because the marginal revenue exceed the marginal cost of the use of an additional allowance. On the opposite, farms with low shadow prices would find it convenient to reduce its emissions and become a seller of CO_2 credits (Stavins, 2010). Assuming perfect competition conditions, ETS would permit both suppliers and buyers to reach potential benefits or cost savings, in a social net benefit maximization perspective (Coase, 2013; Helm, 1998). Currently, the agricultural sector is not included in the European Union Emissions Trading System (EU-ETS), because of the difficulties in the quantification of the emission at the farm-level. Nevertheless, it is noted that the CO_2-shadow prices calculated in this study are much higher than the current EU market price allowances (equal to 5.04 €/t CO_2-eq (June 2017), which was deeply decreased by the surplus of emission credits due to the global economic recession of last decade, and compared with other EU farms. In this regard, Perez (2003) and De Cara and Jayet (2011) estimate a marginal abatement cost among the EU Member States, respectively, in a range of between 35 and 125 EUR/t CO_2-eq 32–42 €/t CO_2-eq for the 10% reduction in European agricultural emissions. However, the results of this study are in line with the estimates reported in other studies. Wettemann and Latacz-Lohmann (2017) estimate an average abatement cost in German dairy farms equals to € 164.97/t CO_2-eq, within a range from 48.14 €/t CO_2-eq to 381.94 €/t CO_2-eq, while MacLeod et al. (2010) quantifies a cost of £ 100/t CO_2-eq for reducing emissions from crops in the UK. Thus, the implementation of an ETS for the agricultural sector seems to be a suitable instrument to seek emission abatement throughout economic incentives, taken into consideration the large differences between farms and between agricultural sector and other sectors (He and Ou, 2017). In this perspective, our results, together with those above mentioned, could represent a pricing benchmark for the implementation of an effective agricultural ETS scheme. In fact, from the Graphic 1, it's possible to determine the CO_2 credit price associated with the introduction of an ETS scheme, where the total amount of allowances, in terms of ton CO_2-eq/ton of milk, is fixed at different levels on the x-axis. Obviously, as the amount of emissions per ton of CO_2-eq (emission intensity) increases, a decrease in the shadow price of CO_2-eq is observed. This result is in line with what has been found by Li et al. (2016) on CO_2-eq emissions related to energy in the European agricultural sector.

If the marginal abatement costs are compared with the CO_2-eq efficiency score (Graphic 2), it is possible to see how, similarly to Choi et al. (2012) findings, there is a positive relationship between the two variables. Therefore, the higher the environmental efficiency is, the higher the cost that the farm will face to reduce its emissions; conversely, the lower the CO_2-eq efficiency score is, the



Graphic 1. Relationship between CO_2-eq emission intensity and CO_2-eq shadow price.



Graphic 2. Relationship between CO_2-eq emission efficiency and CO_2-eq shadow price.

lower the costs associated with the reduction is.

4. Conclusions

A non-radial SBM-DEA model with the undesirable output (CO_2-eq emissions) is implemented to assess input and output efficiency, emission reduction potential and its related marginal cost of abatement in 10 dairy farms in the Umbria region (Italy). The results show significant differences in the efficiency scores computed, which highlight the range of potential reductions in the use of inputs and CO_2-eq emissions differing within dairy farms. In particular, 6 farms are SBM efficient and therefore have no margins on the efficiency of their production process or the use of inputs that produce bad output, as they are already along the efficient frontier. For the other 4 farms, however, there is no full efficiency, with scores ranging from 0.52 to 0.64. Considering separately the efficiency for single inputs and outputs compared to these 5 farms, it can be seen how efficiency scores for Utilised Agricultural Area, Capital and Work are on average lower than those for Feed and Livestock Units. Compared to the use of these two factors, Umbrian farms seem to have reached a high and homogeneous level of performances. On the other hand, in relation to the Utilised Agricultural Area, Capital and Labour, it seems necessary to adopt, for inefficient farms, actions aimed at reducing their employment to achieving farms along the frontier. From this point of view, these results provide a relevant and timely support in orienting strategic business choices, both technical and economic, in the medium and long-term. The identification of the main critical points and the exact quantification of the potential for reduction, and consequently the relative cost savings in production, is a prime source of information available to livestock management.

For CO_2-eq emission efficiency, the performance of the 4 non-SBM efficient farms varies from 0.543 to 0.737, with a reduction potential ranging from 45.7% to 26.3% of CO_2-eq. In absolute terms, the projection of inefficient farms along the frontier would save CO_2-eq emissions of 3808.65 tons, which is about 17.9% of the total for the entire sample. These results show that half of the sample farms present improved environmental performance, highlighting the need to encourage the use of low emissions technologies and measures to bridge existing gaps with the more virtuous farms. Simultaneous technical and environmental improvements could be reach, for example, through the implementation of specific investment measures within the European Union (EU) rural development policy framework (Li et al., 2016). On the other hand, they provide useful support for benchmarking in relation to the environmental efficiency of the regional dairy livestock sector, with the aim of policy regulation (Iribarren et al., 2011).

The dual model of SBM-DEA has shown how the CO_2-eq shadow prices in Umbrian dairy farms are higher than that estimated in several studies that considered the agricultural sector in the EU (De Cara and Jayet, 2011; Perez, 2003). This result highlights how the sector is already at an advanced stage in the transition to low carbon production. Several previous studies (Du et al., 2015; Morris et al., 2012; Zhou et al., 2013) found the negative relationship linking the abatement cost and the emission intensity. Consequently, the adoption of compensatory measures in the context of European emission control policies appears to be economically unsatisfactory if low emission intensity levels are to be achieved (Li et al., 2016). In addition, the positive relationship that characterizes the trend of the shadow price of CO_2-eq compared to CO_2-eq efficiency highlights how farming with high environmental performance are even those who are forced to pay more for cutting emissions. Possible inclusion of the agricultural sector within a carbon credit system at EU level would allow farms with abatement costs higher than the market price to buy emission allowances and vice versa to make profits from the sale of credits to those farms that can reduce their emissions at lower cost than the market price. In this perspective, the estimated marginal abatement costs could together with those above mentioned, could represent a pricing benchmark for the implementation of an agricultural ETS scheme.

Far from wanting to extend the results of this study to a complex context such as global climate policy, the paper aims to propose and favour the use of SBM-DEA with emissions of CO_2-eq as a useful tool for guiding farmers decisions, as well as providing ideas for policy action in the environmental field.

The main critical point of the study is the limited sample size, which could affect the accuracy of efficient frontier estimation. However, given the small-scale dimensions of the study area analyzed, it can be reasonably assumed that the sample considered is sufficiently representative of Umbrian dairy farms and that the obtained results can be extended to the study area.

Another possible limitation is related to the deterministic nature

of the DEA approach to efficiency assessment, that does not allow for the measurement of errors, to the detriment of the internal and external validity of the results obtained.

Possible developments of this work may be the enlargement of the number of farms considered and the inclusion in the model of more and detailed input categories. For example, the specification of the single feed input could provide more precise operating instructions with a view to eliminating excessive use. Moreover, the inclusion in the model of uncertainty analysis such as bootstrapping algorithms or sensitivity analysis could increase the robustness of the estimates.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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